China Economic Review 74 (2022) 101809

Contents lists available at ScienceDirect

China Economic Review

journal homepage: www.elsevier.com/locate/chieco

China's skill-biased imports☆

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ARTICLE INFO

Jel code:
F16
J20
J31
O33

Keywords:
Imported capital goods
Skill-biased technological change
Skill premium

ABSTRACT

China has witnessed rapid increases in the skill premium over the last few decades. In this paper, we study the short-run effect of capital goods imports on skill premium in China. The surge in capital goods imports, which embody advanced technology, can explain the rising demand for skill in China. We exploit regional variations in capital goods import exposure stemming from initial differences in import structure and instrument for the capital goods import growth using exchange rate movements. A city at the 75th percentile of the distribution of capital goods imports growth has a higher skill premium by 5 percentage points (0.38 standard deviation) over the one at the 25th percentile. To explore the underlying mechanism, we provide firm-level evidence and show that imported capital goods are skill-complementary.

1. Introduction

This paper studies the labor market consequences of capital goods imports, an important measure of imported technology (Burstein, Cravino, & Vogel, 2013; Parro, 2013; Raveh & Reshef, 2016). While skill-biased technological change has been identified as one of the major driving forces for the rising demand for skills in developed countries (e.g., Katz & Autor, 1999; Katz & Murphy, 1992), less is known about its impact on the labor markets in developing countries. For developing countries, technological advances mainly come from the adoption of foreign technologies. In this paper, we show that imported capital goods, which embody advanced technology, increase skill premium in developing countries like China.[1]

We show that importing skill-complementary capital goods drives up the demand for skilled workers and increases skill premium,

☆ We thank Pietro Biroli, Lorenzo Casaburi, David Dorn, Peter Egger, David Hémous, Nir Jaimovich, Will Kohler, Devashish Mitra, Ralph Ossa, Dina Pomeranz, Ariell Reshef, Hannes Schwandt, Xinzheng Shi, Asha Sundaram, Yongjin Wang, Fabrizio Zilibotti, Josef Zweimüller and participants in various seminars and conferences for valuable comments. We thank China Data Center of Tsinghua University and Qiong Zhang for data support. Fundings by the German Research Foundation (DFG) through CRC TR 224 (Project B06) and the Swiss National Science Foundation (grant BSSGIO_155804) are gratefully acknowledged by Lei Li.

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[1] Katz & Murphy (1992); Berman et al. (1994); Bekman, Bound, & Machin (1998); Acemoglu (1998, 2003); Autor et al. (2003) show that skill-biased technical change is one of the major driving forces for U.S.'s rising skill premium. The trade literature stresses that trade in intermediate inputs and offshoring can also drive up the demand for skills in both developed and developing countries (Acemoglu, Gancia, & Zilibotti, 2015; Feenstra & Hanson, 1996, 1997, 1999; Grossman & Rossi-Hansberg, 2008; Hummels et al. (2014). In particular, Burstein et al. (2013); Parro (2013); Fan (2019) discuss the imported capital goods channel from a theoretical perspective. Raveh & Reshef (2016) use cross-country data, and Koren & Csillag (2019) use firm-worker data to examine this channel.

https://doi.org/10.1016/j.chieco.2022.101809
Received 9 November 2021; Received in revised form 16 April 2022; Accepted 11 May 2022
Available online 2 June 2022
1043-951X/

as capital and skill are complementary in production (Krusell et al., 2000). China offers a particularly suitable setting to study this topic, as it is the largest developing country that has witnessed rises in both capital goods imports and demand for skilled labor. Indeed, Fig. 1 shows a simultaneous rise in the skill wage premium, i.e., the wage gap between workers with a college degree and those without, and the amount of high-skilled workers in China during the 1990s and 2000s, implying an increasing demand for skilled workers. Fig. 2 shows some macro trends, suggesting that the imports of capital goods took off in the 1990s, around the same time when the skill premium started to rise.

Empirically, we exploit city-level variations in skill premium using the Urban Household Survey data and import exposure using the administrative trade record from China's Customs Office. To tackle causality, we use the city-level exchange rate exposure as the instrumental variable for capital goods imports. Because RMB was pegged to USD, a change in the exchange rate between the U.S. dollar and Euro would cause the RMB/Euro exchange rate to move exogenously. As different cities import from different countries, they are subject to exchange rate shocks to different degrees, which is the source of identification in our empirical work. In the robustness check, we exclude China's imports from the United States and trade partners whose currencies are pegged to the U.S. dollars. Our first-stage regression results demonstrate that exchange rate movements are highly correlated with China's capital goods imports, and they pass the weak instrument tests.

We find that importing capital goods is indeed a key factor driving up the skill premium in China. An increase in local penetration of capital imports, defined as the share of the accumulated capital imports over total capital stock, by one standard deviation increases the skill premium by 14 percentage points. Specifically, a city at the 75th percentile of the distribution of capital goods import intensity would have a skill premium 5.3 percentage points higher (0.38 standard deviation) than that of a city at the 25th percentile. The effect on the skill wage premium is larger for capital goods sourced from R&D-intensive countries, echoing the work of Raveh & Reshef (2016). Using a cross-country sample, Raveh & Reshef (2016) show that countries importing more R&D-intensive capital goods have higher skill premium.

Employing firm-level data, we provide direct evidence that imported capital equipment drives up demand for skills. By linking the Annual Survey of Industrial Production (ASIP) data with the administrative record from China's Customs Office, we show that firms importing more capital goods hire more skilled workers, use computers more intensively, pay higher wages, and have higher labor productivity. These findings confirm capital-skill complementarity, as documented in Griliches (1969), Goldin & Katz (1998), and Krusell et al. (2000). To further confirm the complementarity between skill and imported capital equipment, we use the employer-employee matched data in 2015 to show that operators of imported machines earn more than domestic machine operators in the same firm. In Hungary, imported machine operators also enjoy wage premium. Koren & Csillag (2019) show that Hungarian workers who operate imported machines earn more than ordinary workers.

Can other trade-related channels explain the rising skill premium in China?[2] While we focus on imported technology or how technological change has happened in China, previous trade literature can explain why China has imported technology (Goldberg, 2015; Goldberg & Pavcnik, 2007; Pavcnik, 2017). Offshoring or FDI could increase the demand for skilled workers if the offshored parts or tasks are relatively more skill-intensive in the recipient developing countries (Feenstra & Hanson, 1996, 1997, 1999; Hsieh & Woo, 2005). Access to foreign markets may also encourage exporters to upgrade technology (Bustos, 2011a, 2011b;Verhoogen, 2008; Zhu & Trefler, 2005). The above theories do not contradict our explanation because importing capital goods could facilitate the offshoring practices in developing countries by multinationals. Empirically, both offshoring and exports would predict exporting firms to be more skill-intensive than other firms. In Table 1, we find that exporting firms were indeed more skill-intensive than non-exporting firms in 2014. However, they were less skill-intensive than non-exporting firms in 2004. Results in Table 4 also suggest that during our sample period (1998–2009) when China was at the early stage of globalization and exports were labor-intensive, imported capital goods were more likely to be the driving force for the rising skill premium in China.[3] Besides, skill improvements due to importing inputs (Crinò, 2012; Chen, Yu, & Yu, 2017) and technology upgrades due to access to the foreign market and import competition (Attanasio, Goldberg, & Pavcnik, 2004; Autor et al., 2020; Bloom, Draca, & Van Reenen, 2016; Lu & Ng, 2013; Pavcnik, 2003; Wood, 1995) may also drive up demand for skills. In the robustness checks, we will address these concerns.

The rest of the paper is organized as follows. Section 2 illustrates the empirical model and the identification strategy. Section 3 introduces the data and documents the data patterns. Section 4 and section 5 present the empirical results. Section 6 concludes.

2. Empirical approach

2.1. Econometric specification

We rely on city-level variations to identify the impact of capital goods imports on the local skill premium

[2] Classical trade models, such as the Stolper-Samuelson theorem, would predict a narrowing wage gap in a labor-abundant developing county such as China.

[3] In Table 1, the skill share of capital goods importers was much higher than other firms, while the skill shares of exporting firms and non-exporting firms were similar in 2004. In 2014, however, the skill share of exporters was much higher than that of non-exporters. The descriptive evidence suggests that both offshoring and export were not the major driving forces for the rising skill premium in China during the early stage of trade openness, while they have played growing role in driving up the skill premium as time goes by.

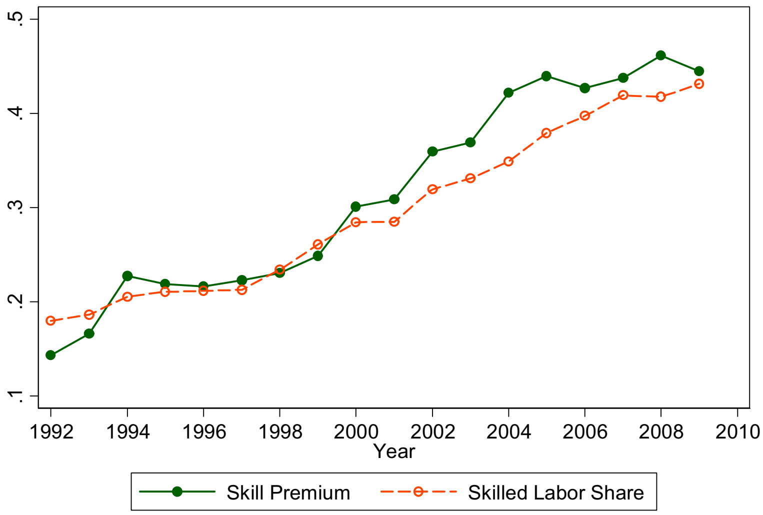

Fig. 1. Skilled labor share and skill premium.
Data: Urban Household Survey, 1992–2009.
Note: Skilled labors are defined as workers (aged between 16 and 60) with college degrees or above (15 years education or more). Skill labor share is defined as the share of skilled workers among all employed workers in urban China. People who are not in the labor force or remain unemployed are not included. College premium is estimated based on Mincer-style OLS regression after we control for gender, working experience and its square term, employer ownership type, and industry dummies.

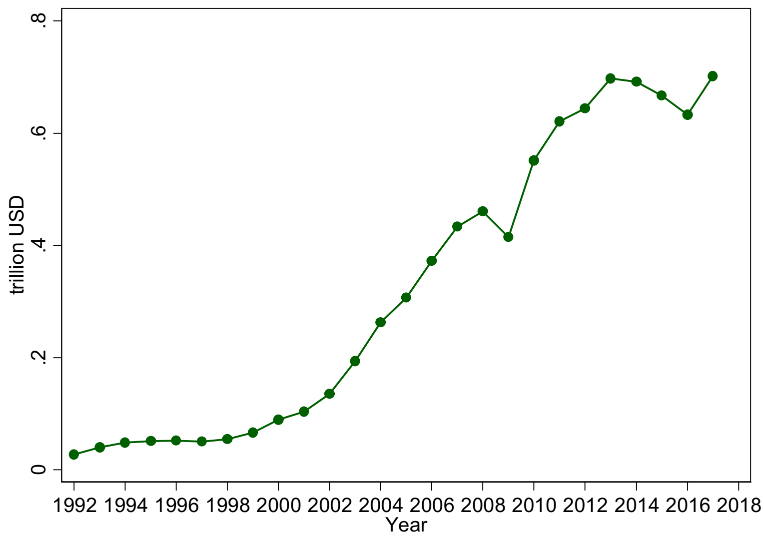

Fig. 2. China's import of capital goods.
Data: UN Comtrade Database, 1992–2017.
Note: This figure shows the pattern of Chinese total imported capital goods (unit: 1 trillion US$). We define capital goods to be the sum of ISIC Rev. 3 codes 29–33, excluding those that do not belong to Broad Economic Classification (BEC) industry 41 (capital goods) and BEC industry 42 (parts and accessories of capital goods) and adding those that belong to BEC industry 521 (transportation equipment used for the industry).

$$y_{it} = \alpha \frac{K_{it}^{IM}}{K_{it}} + X_{it}\delta + Z_{jt}\lambda + \mu_i + \gamma_t + \varepsilon_{it}, \tag{1}$$

where subscripts i and t denote city and year, respectively. y_{it} is the skill premium at the city-year level. $\frac{K_{it}^{IM}}{K_{it}}$, the capital goods imports intensity, is defined as the share of the accumulated capital imports K_{it}^{IM} over total capital stock K_{it}. X_{it} includes a rich set of city-level covariates. μ_i and are γ_t city and year fixed effects, respectively, which capture time-invariant city characteristics and macro shocks. To capture region-specific time-varying characteristics, we also include a measure for regional time trends, z_{jt}. Models are weighted by the start-of-period city-level population. Standard errors are clustered at the city level. A positive coefficient α would indicate that

Table 1
Employment structure by education among manufacturing firms.

	College degree or above	Senior high school degree	Junior high school degree or below
Panel A: ASIP 2004			
Firms with imported machine	0.19	0.37	0.44
Firms without imported machine	0.11	0.32	0.57
Panel B: CEES 2014			
Firms with imported machine	0.18	0.33	0.49
Firms without imported machine	0.14	0.34	0.52
Panel C: ASIP 2004			
Exporting Firm	0.11	0.31	0.59
Non-exporting Firm	0.12	0.33	0.55
Panel D: CEES 2014			
Exporting Firm	0.17	0.32	0.51
Non-exporting Firm	0.14	0.36	0.50

Data: Annual Survey of Industrial Production (ASIP, 2004) and China Employer-Employee Survey (CEES, 2014).
Note: ASIP data is the Annual Survey of Industrial Production data in 2004. CEES data is the China Employer-Employee Survey data in 2014.

imported capital goods have a positive impact on the skill premium.

2.2. Skill premium

To measure the city-level skill premium in Eq. (1), we estimate a Mincerian wage regression (Mincer, 1974) separately for each city in each year:

$$ln\left(w_j^{it}\right) = \beta_1^{it}S_j^{it} + \beta_2^{it}E_j^{it} + \beta_3^{it}\left(E_j^{it}\right)^2 + \beta_4^{it}M_j^{it} + \mu_j^{it} + \gamma_j^{it} + \varepsilon_j^{it}, \tag{2}$$

where $ln(w_j^{it})$ is the log value of wage for individual j in city i and year t.[4] S_j^{it} is an indicator for college education (i.e., S_j^{it}=1 if worker j holds a college degree or above, and 0 otherwise). E_j^{it} denotes an individual's working experience. M_j^{it} is an indicator for males. μ_j^{it} indicates the employer's ownership type (state, collective or private). γ_j^{it} includes a set of dummies indicating the sector that worker j is in. Based on Eq. (2), the estimated coefficient $\widehat{\beta}_1^{it}$ gives the skill premium for city i in year t—i.e., the dependent variable for Eq. (1).

2.3. Import intensity of capital goods

The key independent variable $\frac{K_{it}^{IM}}{K_{it}}$ in Eq. (1), the import intensity of capital goods, is defined as the share of the accumulated capital imports over total capital stock. We employ a perpetual inventory method to calculate it:

$$\frac{K_{it}^{IM}}{K_{it}} = \frac{(1-\rho)K_{it-1}^{IM} + K_{it}^{IM:flow}}{K_{it}} \tag{3}$$

where the accumulated capital imports K_{it}^{IM} is the sum of the current year's imports of capital goods and the previous year's accumulated imports of capital goods after depreciation. The rate of depreciation is set at 10% (Kydland & Prescott, 1982). We set 1997 as the initial year since it is the earliest year for which we have city-level trade data.[5] The city-level total capital stock data K_{it} is the aggregate capital stock of industrial enterprises above designated size, obtained from the Annual Surveys of Industrial Production (ASIP).

2.4. Instrumental-variable strategy

Two concerns emerge regarding the OLS estimation of Eq. (1). First, other economic forces may also affect changes in the skill premium. If these factors are also correlated with the choice to import capital goods, this would generate a spurious relationship between capital goods imports and the skill premium. One possible confounding factor is domestic innovation: a region that imports capital equipment may also happen to conduct more R&D itself, resulting in an increase/decrease in skill premium if the R&D activities

[4] Wage is deflated to the 1992 price level.
[5] This means that we assume that the imports of capital goods before 1997 were negligible, which is reasonable since the capital goods imports in China began to surge in 2002 and the total capital goods imports in 1997 was only 37% of that in 2002.

are skill/unskilled-complementary. If this is the case, and domestic innovation is left in the error term, we will over/under-estimate the true impact of capital goods imports. Second, causality may go in the opposite direction. For example, regions with cheaper unskilled workers have less incentive to import skill-complementary capital goods, and thus in this example, it is the skill premium that causes imported capital goods to change. If this is the case, then the OLS estimation may overstate the true effect of capital goods imports on the skill premium.

To address these endogeneity concerns, we identify the impact of imported capital goods on the skill premium by employing the exchange rate as the instrumental variable.[6] The exchange rate movement could be understood as a cost shock: an appreciation of RMB against currencies of city i's source countries lowers the price of imported capital goods, and therefore induces city i to import more foreign capital equipment. As a consequence, the demand for skills will rise because of capital-skill complementarity. To be specific, we use the multilateral real effective exchange rate movements to capture the change in costs of capital goods imports.

Specifically, we estimate the following equation,

$$\frac{K_{it}^{IM}}{K_{it}} = \theta ln(REER_{it}) + X_{it}\delta + Z_{jt}\lambda + \mu_i + \gamma_t + \varepsilon_{it}, \tag{4}$$

where subscripts i and t denote city and year, respectively. X_{it} includes a set of city-level covariates that may also affect the decision to import capital goods. z_{jt} includes regional time trends. Finally, μ_i and γ_t are city and year fixed effects, respectively.

The instrument variable, $ln(REER_{it})$, is the log value of the real effective exchange rate between RMB and a basket of currencies of city i's trading partners, defined as:

$$ln(REER_{it}) = \sum_c \left[\varphi_{i,c,t-i} \times ln\left(RER_{c,t}\right)\right] = \sum_c \left[\frac{k_{i,c,t-1}}{\sum_c k_{i,c,t-1}} \times ln\left(\frac{e_{c,t}}{P_{China,t}/P_{c,t}}\right)\right], \tag{5}$$

where subscripts i, c, and t denote city, country, and year, respectively.[7] Thus, $REER_{it}$ is a geometrically weighted average of the bilateral real exchange rate, $RER_{c,\ t}$. The weight $\varphi_{i,\ c,\ t-1}$is city i's lagged import shares of capital goods stock $k_{i,\ c,\ t-1}$ from country c, which measures the importance of capital goods imported from country c. $RER_{c,\ t}$ is the real exchange rate between RMB and country c's currency in year t, calculated as the bilateral nominal exchange rate $e_{c,\ t}$ deflated by relative price indices. Note that $e_{c,\ t}$ is defined as foreign currency per unit of RMB. Therefore, a higher RER indicates that RMB appreciates against the currency of foreign country c.

Clearly, the exposure to exchange rate shocks varies across cities. This variation arises from two sources. First, different cities import from different sources; for example, cities in Northeastern China import relatively more from Japan and Korea, while cities in South China import more from Southeast Asia countries. Second, different cities also have different industry structures and therefore the import weights change across cities.[8]

3. Data

Our empirical investigation is built on a rich set of micro-level data, including information on wages and employment status, exports, imports, and balance sheet information for manufacturing firms.

3.1. Household survey and skill premium

We draw on the Urban Household Survey (UHS) from 1992 to 2009 for information on wages and jobs. The UHS is by far the most comprehensive household survey with the most extended time coverage in China. It offers detailed records on demographics, employment, income, taxes, and social security information for urban households. To ensure representativeness, the National Bureau of Statistics of China (NBSC) adopts a probabilistic and stratified multistage sampling method when selecting households. Because similar sampling methods and questionnaires have been used for each wave of the survey, the data is comparable over time and across regions. We obtain access to the UHS covering 18 provinces, which are representative in terms of geographic location and the level of economic development.[9] For our purposes, we focus on individuals who are between 16 and 60 years old and have labor income. In the empirical analysis, we use data from 1998 due to the limitation of trade data.

The wage premium for skilled workers shot up in China between 1992 and 2009. It remained around 20% in the late 1990s and then

[6] Exchange rate movements are generally considered as exogenous shocks affecting trade flows and are widely used in trade literature (Alfaro, Alejandro, Fadinger, & Liu, 2017; Bastos, Silva, & Verhoogen, 2018; Bustos & Rotemberg, 2017; Campbell, 2016; Dai & Jianwei, 2017; Park, Yang, Shi, & Jiang, 2010).

[7] Similar instruments using exchange rate fluctuation have been adopted in previous research such as Bastos et al. (2018).

[8] In Fig. 6, we show that a city with increasing REER (i.e., appreciating against trade partners) tends to import more capital goods. Appendix Table A.2 shows that the correlation of city's import share from major source countries are generally very low. For example, the correlation between import share from Japan versus Korea is about −0.02. These correlations suggest that cities have their own major sourcing countries and therefore are exposed to exchange rate shocks.

[9] The 18 provinces include coastal provinces (Beijing, Guangdong, Jiangsu, Liaoning, Shandong, Shanghai, and Zhejiang), and inland provinces (Anhui, Chongqing, Gansu, Heilongjiang, Henan, Hubei, Jiangxi, Sichuan, Shaanxi, Shanxi, and Yunnan).

rose rapidly to 44% in 2009 (Fig. 1). Note that the wage premium for skilled workers increased despite a dramatic increase in the supply of skilled workers due to the massive college expansion since 1999 (Li, Li, Binzhen, & Xiong, 2012; Li, Loyalka, Rozelle, & Binzhen, 2017). The change in skill premium also diverges across regions. Fig. 3 shows the return to college education across three different regions (i.e., the East, Central, and West). Before 2001, changes in skill premium manifest a similar trend across regions. For example, in 1992, skilled workers (workers with college degrees) earned about 13% more than unskilled workers (workers without college degrees), regardless where they resided, while in 2001 skilled workers in different locations earned about 29% more than unskilled workers. The skill premium, however, started to diverge across regions in 2001 when China entered the WTO. In 2009, for example, the skill premium in eastern cities reached 46%, while that of central and western China stayed at around 31% and 38%, respectively.

For the city-level skill premium used in the empirical analysis, we present the summary statistics in Table 2. From 1998 to 2009, the average skill premium in urban China is about 32% (standard deviation: 14%), with an inter-quartile range of 0.23 to 0.41.[10]

3.2. Trade data and import intensity

3.2.1. Trade data

Data on imports of capital goods and intermediate goods by Chinese cities from different source countries, as well as exports, at six-digit HS categories, are collected by the General Administration of China Customs (GACC), for the period 1997 to 2009. For a sub-period of 2000–2006, we also have firm-level export and import information. In later extensions, we match the firm-level trade data with balance sheet and production information provided in the Annual Surveys of Industrial Production (ASIP). Finally, for the purpose of comparison, we also collect trade data for other countries from the UN Comrade Database.

Capital goods—such as computers and machinery—are durable goods that are used in the production of goods or services. We follow Burstein et al. (2013) and define capital goods based on the International Standard Industrial Classification (ISIC-rev.3) and Broad Economic Classification (BEC).[11]

China has seen some very fast growth in capital goods imports in the last few decades. As shown in Fig. 2, China only imported capital goods with a value of 27 billion U.S. dollars in 1992, but the value increased rapidly to 702 billion U.S. dollars in 2017. During our sample period (1998–2009), the average annual growth rate was over 20%, with accelerated growth since 1998.[12]

As a result, China has become one of the largest importers of capital goods in the world. As shown in Fig. 4, in 1992, the share of capital goods in China's total value of imports was 34%, which is 9 percentage points larger than the average of seven developed countries, including France, Germany, Italy, Japan, Korea, the United Kingdom, and the United States. By 2017, the gap rose to 13%. China's share is also well above the average level of the other four BRICS countries, including Brazil, India, Mexico, and Russia.

China imports capital goods mainly from advanced economies, with imports from Japan, Taiwan, Korea, the United States, and Germany accounting for nearly 70% of the total value of capital goods imports from1997 to 2009 (Appendix Table A.1).

3.2.2. Firm-level data

To provide additional evidence for capital-skill complementarity, we examine firms' usage of capital goods using two firm-level surveys. The first survey is the Annual Survey of Industrial Production (ASIP), collected by the NBSC. This dataset contains the balance sheet and production information for all state-owned enterprises (SOEs) and all non-state firms with annual sales above 5 million RMB, in mining, manufacturing, and public utility sectors.[13] In addition, the 2004 version of the survey, as part of the 2004 industrial census of China, reports employment by workers' education and also the number of computers used by each firm.

The second firm survey we use is the China Employer-Employee Survey (CEES), which is an employer-employee linked survey conducted in China. We have access to the 2015 wave, which was conducted in Guangdong province and included about 500 firms and 4000 employees. One advantage of this data is that we can directly observe the wages of machine operators and other workers, the value of machines, and whether the machines are imported.

3.2.3. Macro data

To construct our instrumental variables, we need to use the country-to-country bilateral real exchange rates, as well as city-level

[10] For the rising skill premium in China, related literature includes Hsieh and Woo (2005); Han, Liu, & Zhang (2012); Chen, Yu, & Yu, 2017; Ge, Yang, & Tech (2014); Sheng & Yang (2017).

[11] Specifically, capital goods include products that belong to the ISIC Rev. 3 codes 29–33, excluding those that are not belong to Broad Economic Classification (BEC) industry 41 (capital goods) and BEC industry 42 (Parts and accessories of capital goods) and adding those that belong to BEC industry 521 (transportation equipment used for industry). In ISIC Rev. 3, 29 refers to manufacture of machinery and equipment n.e.c; 30 refers to manufacture of office, accounting and computing machinery; 31 refers to manufacture of electrical machinery and apparatus n.e.c; 32 refers to manufacture of radio, television and communication equipment and apparatus; 33 refers to manufacture of medical, precision and optical instruments, watches and clocks.

[12] Between 1992 and 2017, the average annual growth rate was 14%.China is also one of the major producers of capital goods. However, more than 50% of Chinese exports in capital goods are processing trade. For example, the computers industry, processing exports account for over 95% of total exports. Furthermore, products exported by industrial countries appear to be higher quality than those from developing countries such as China (Schott, 2008).

[13] As documented in Brandt, Van Biesebroeck, & Zhang (2012), firms in the ASIP dataset account for 90%, 91%, 97% and 70% of the gross asset, sales, export, and employment respectively in the manufacturing sector.

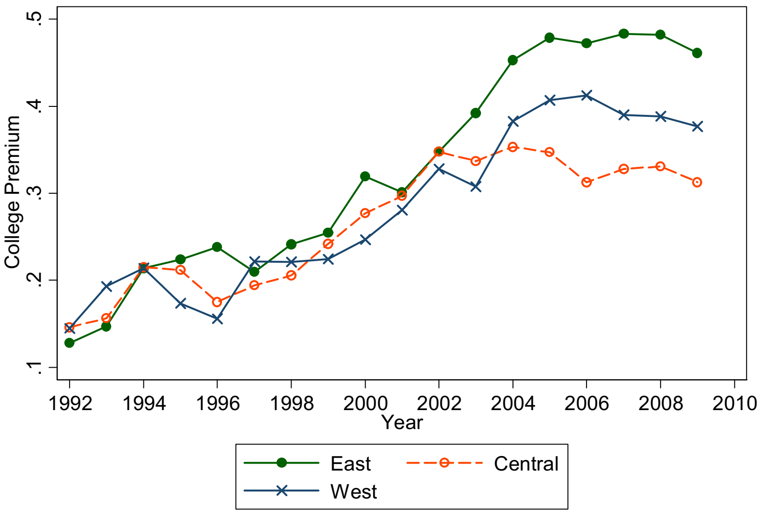

Fig. 3. College premium by region.
Data: Urban Household Survey, 1992–2009.
Note: College workers are defined as workers (aged between 16 and 60) with college degree or above (15 years education or more). College premium is calculated based on Mincer-style OLS regression after we control for gender, working experience and its square term, firm ownership type, and industry dummies. Following the regional classification by China's National Bureau of Statistics, Eastern China includes Beijing, Guangdong, Jiangsu, Liaoning, Shandong, Shanghai, and Zhejiang, central China includes Anhui, Heilongjiang, Henan, Hubei, Jiangxi, and Shanxi, and western China includes Chongqing, Gansu, Sichuan, Yunnan and Shaanxi.

Table 2
Summary statistics.

Variable	Mean	sd	P25	Median	P75	N
Panel A: City-level (UHS & CGAC, 1998–2009)						
Skill Premium	0.32	0.14	0.23	0.32	0.41	1670
Imported Capital Goods Intensity	0.33	0.67	0.04	0.11	0.29	1670
Export/GDP	0.15	0.28	0.03	0.06	0.17	1670
(Export+Non-Capital Goods Import)/GDP	0.23	0.41	0.04	0.10	0.28	1670
Panel B: Firm data (CEES, 2014)						
Ln(Monthly wage), thousand RMB	1.24	0.35	1.10	1.22	1.39	3959
Share of College Workers	0.24	0.43	0.00	0.00	0.00	3959
Operator of imported machine (dummy)	0.09	0.28	0.00	0.00	0.00	3959
Operator of machine (dummy)	0.37	0.48	0.00	0.00	1.00	3959
Use PC at work (dummy)	0.66	0.47	0.00	1.00	1.00	3959
Panel C: Firm Data (ASIP, 2004)						
Share of College Workers	0.11	0.16	0.02	0.06	0.15	216,932
Number of Computer per Worker	0.07	0.12	0.01	0.04	0.09	216,932
Ln(Average Wage), thousand RMB	2.47	0.62	2.11	2.49	2.84	1,482,241
Ln (Value-added per Worker)	4.01	1.00	3.32	3.93	4.63	1,482,241
Imported Capital Goods (flow)/Capital	0.01	0.06	0.00	0.00	0.00	1,482,241
Export/Sales	0.16	0.33	0.00	0.00	0.03	1,482,241
Non-capital goods import/Input	0.02	0.10	0.00	0.00	0.00	1,482,241
Ln (Employee)	4.72	1.08	3.95	4.61	5.35	1,482,241

Data: Urban Household Survey (UHS, 1998–2009), China General Administration of Customs (CGAC, 1998–2009), Annual Survey of Industrial Production (ASIP, 2004), and China Employer-Employee Survey (CEES, 2014).
Note: The statistics in Panel A are weighted by each city's population in 1998. We use the inversed sampling probability as weights for statistics in Panel B. In Panel C, data about share of college workers and number of computer per worker are only available in 2004. The time span for expenditure on new product or R&D to output ratio is from 2005 to 2007. The time span for the rest is from 2000 to 2007.

macro indicators. We collect real exchange rates from the Penn World Table (PWT 7.0, 1997–2009). In addition, we collect the city-level gross regional product (GRP), city-level capital stock, provincial-level FDI inflow, and consumer price index (CPI) from China Statistical Yearbooks and China City Statistical Yearbooks (1998–2009).

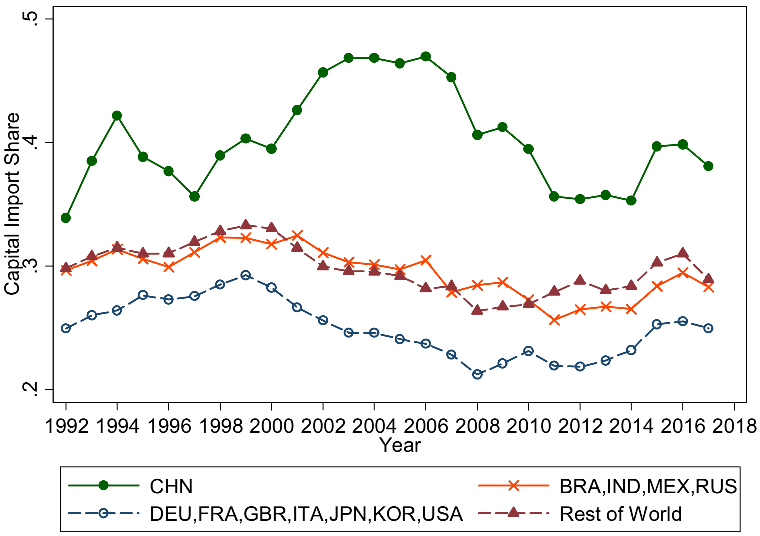

Fig. 4. Cross country comparison of imported capital goods as share of total imports.
Data: UN Comtrade Database, 1992–2017.
Note: Capital goods are defined as the sum of ISIC Rev. 3 codes 29–33, excluding those that are not belong to Broad Economic Classification (BEC) industry 41 (capital goods) and BEC industry 42 (Parts and accessories of capital goods) and adding those that belong to BEC industry 521 (transportation equipment used for industry). The seven developed countries include France (FRA), Germany (DEU), Italy (ITA), Japan (JPN), Republic of Korea (KOR), the United Kingdom (GBR), and the United States (USA). The four developing countries include Brazil (BRA), India (IND), Mexico (MEX), and Russia (RUS).

4. Capital goods imports and skill premium

In this section, we examine whether capital goods imports can explain the rising demand for skilled workers by exploring city-level variations. Before reporting city-level regressions, we first present how skill wage premia and capital goods imports vary across the three regions of China (i.e., the East, Central, and West).

There are large variations in both the skill wage premia and capital goods imports across regions, and the two seem to be related. At the regional level, there are substantial variations in the imports of capital goods. The share of capital goods in total imports is much larger in Eastern China than in Central and Western China, and the trends of growth in different regions are also quite divergent (Fig. 5). Skill premia also started to diverge across regions in the early 2000s as shown in Fig. 3, with those in Eastern China becoming much higher than those in other regions.

4.1. Exchange rates and imported capital goods

The identification idea is that an exogenous appreciation of RMB against other currencies will increase China's imports of capital goods. This relationship is clear in Fig. 6. For example, as shown in the top left panel, China's imports of capital goods from the U.S. relative to France (dashed line) follow closely the exchange rate movement of the U.S. dollar against the Euro (the solid line) from 1997 to 2009. The patterns are similar for the U.S. vs. Germany, Japan vs. Germany, and the U.S. vs. Korea, indicating that more capital goods are imported from one country relative to the other when it is cheaper to do so.

Our estimation of Eq. (4), the first-stage equation, yields similar results; i.e., appreciating RMB vs. USD increases China's imports of capital goods. Column (1) of Table 3 reports a simple regression with capital goods imports as the dependent variable and REER as the key independent variable. City fixed effects, year fixed effects, and regional time trends are also controlled. The coefficient on REER is positive and significant at the 1% level, suggesting that the city-level weighted exchange rate is positively associated with the intensity of capital goods imports.

To test the validity of the instrumental variable, the capital-goods-import-weighted exchange rate, we run two sets of counterfactual tests. First, we test whether exchange rates weighted using exports or non-capital goods imports can also explain capital goods imports. If they do, then our IV is likely to be invalid. In Column (2), we add as an independent variable the export-weighted exchange rate. Supposedly, the export-weighted exchange rate should not affect imports of capital goods, especially when we also have capital-goods-import-weighted exchange rate included in the regression. Indeed, only our IV can explain capital goods imports, but not the export-weighted exchange rate, which is not statistically significantly different from zero. In Column (4), we also include the non-capital-goods-weighted exchange rate, and again it cannot explain the variation of capital goods imports, while the result for the capital-goods-weighted exchange rate remains. These results suggest that our IVs are valid.

Second, we test whether our IV is correlated with other trade variables such as exports or imports of non-capital goods. In Column (3), we switch to the dependent variable, exports as a percent of the cities' total value-added, or GRP (Gross Regional Product). As

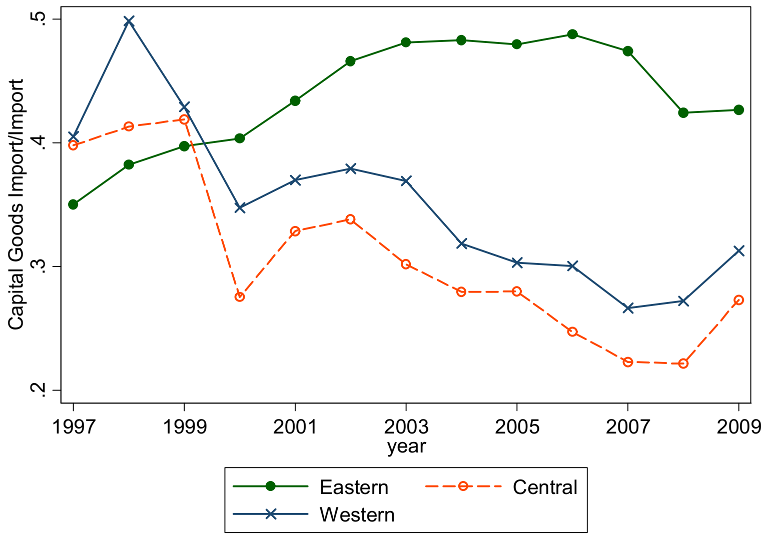

Fig. 5. The share of capital goods in total imports by region, 1997–2009.
Data: China General Administration of Customs, 1997–2009.
Note: Following the regional classification by China's National Bureau of Statistics, Eastern China includes Beijing, Guangdong, Jiangsu, Liaoning, Shandong, Shanghai, and Zhejiang, central China includes Anhui, Heilongjiang, Henan, Hubei, Jiangxi, and Shanxi, and western China includes Chongqing, Gansu, Sichuan, Yunnan and Shaanxi.

expected, RMB appreciation reduces exports, but the capital-goods-import-weighted exchange rate is uncorrelated to exports. The results are similar when we use non-capital goods imports relative to GRP (Gross Regional Product) as the dependent variable (Column (5)). These results again show that the capital-goods-import-weighted exchange rate is a viable instrumental variable.

Finally, our instrumental variables pass the tests for under-identification and weak instruments. We first report the heteroscedasticity-robust Kleibergen-Paap LM statistic (Kleibergen & Paap, 2006) in Column (2) for under-identification and weak instruments. The test statistics reject the null hypothesis that the model is under-identified. We run four tests for weak instruments: the Cragg & Donald (1993) Wald F statistics under the assumption of homoscedasticity, the Kleibergen & Paap (2006) Wald F statistic under the assumption of heteroscedasticity, the Anderson & Rubin (1949) Wald test F statistic, and Stock & Wright (2000) LM statistic. The test statistics reject the null hypothesis that the excluded instruments are jointly equal to zero.[14]

4.2. Capital goods imports and skill premium

We first present the ordinary least squares (OLS) results as a benchmark. In Column (1) of Table 4, we report an OLS regression with the city-level skill wage premium as the dependent variable, and we control for city fixed effects, year fixed effects, and regional time trends. The coefficient on capital goods import intensity is positive and significantly different from zero, suggesting that imports of capital goods have a positive and significant effect on the city-level skill premium. The magnitude of the coefficient is 0.03.

IV regression results confirm that the imports of capital goods have a positive effect on the skill wage premium at the city level. In Column (2) of Table 4, we report the 2SLS results. The coefficient on the imported capital goods intensity variable is positive and significantly different from zero, suggesting that importing capital goods into a city has a positive impact on the city-level skill wage premium. Moreover, the coefficient of the IV estimate is much larger than the OLS estimate, suggesting that the OLS estimate is downward-biased.

The point estimate of 0.21 is also quite large economically. This means when imported capital goods intensity increases by one standard deviation, the skill premium increases by 14 percentage points. Putting this into context, considering a city at the 25th percentile of the distribution of capital goods imports, its skill premium will rise by 5 percentage points ((0.29–0.04)*0.21) or 0.38 of a standard deviation ((0.29–0.04)*0.21/0.14) if its import intensity increases to the level of a city at the 75th percentile. This finding is consistent with a cross-country study by Raveh & Reshef (2016), who finds that an increase in skill-complementary capital goods from the 25th to the 75th percentile could explain about two-thirds of the inter-quartile rise in the skill premium.

One concern with the simple regression reported in Column (2) is that the imported capital goods intensity may have picked up the effect of exports, as cities that import a lot of capital goods may also be large exporters at the same time. The direction of potential bias is ambiguous since the impact of exports on the skill wage premium could go either way. On the one hand, as we discussed before, if a city specializes in exporting labor-intensive goods, then exports may drive up demand for unskilled labor and therefore reduce the skill

[14] While the Cragg-Donald Wald F statistic has critical values tabulated by Stock & Yogo (2005), the Kleibergen and Paap Wald F statistic does not have corresponding critical values. A common practice is to use the Stock-Yogo critical values as benchmarks for both of the two tests.

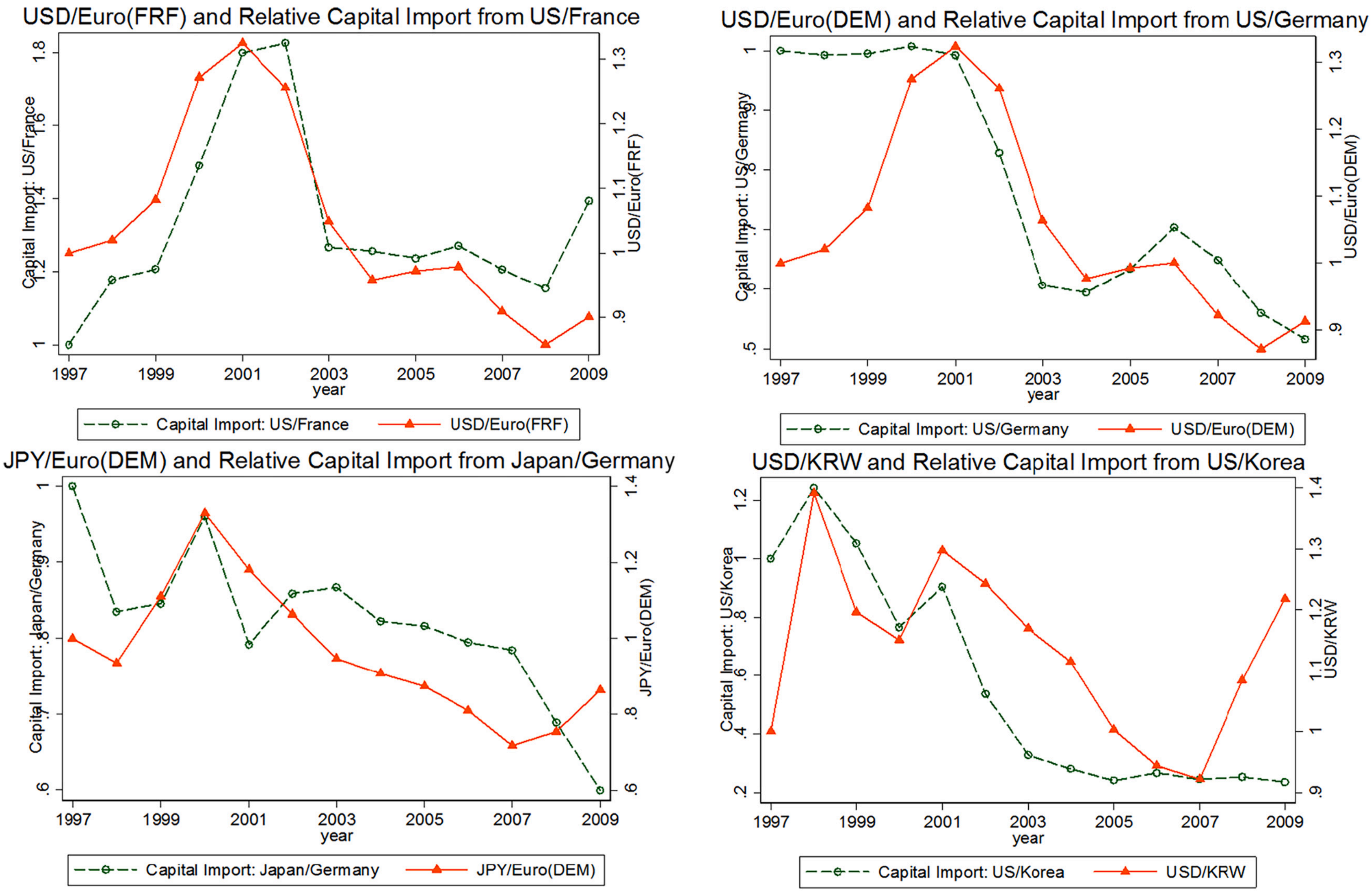

Fig. 6. Relative exchange rates and China's relative imports of capital goods.
Data: Penn World Table (PWT 7.0) and China General Administration of Customs, 1997–2009.
Note: the red solid line presents the exchange rate movement between China's two trading partners (right axis) from 1997 to 2009, and the green dash line shows China's relative imports of capital goods from the two countries (left axis) over the same period. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
First stage.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Imported Capital Goods Intensity	Imported Capital Goods Intensity	Export/ GDP	Imported Capital Goods Intensity	(Non-Capital Goods Import & Export)/GDP
Ln(Exchange Rate)$_{Kstock}$	1.38***	1.41***	0.12	1.41***	0.17
	(0.50)	(0.49)	(0.14)	(0.49)	(0.22)
Ln(Exchange Rate)$_{Export}$		−0.14	−0.49***	−0.14	−0.69**
		(0.35)	(0.17)	(0.35)	(0.27)
Ln(Exchange Rate)$_{Non\text{-}Kimport}$				−0.01	0.03
				(0.07)	(0.06)
Kleibergen-Paap rk LM statistic	6.88***	6.58**	6.58**	5.43*	5.43*
Cragg-Donald Wald F statistic	54.46	6.99	6.99	3.98	3.98
Kleibergen-Paap rk Wald F statistic	7.55	3.36	3.36	1.77	1.77
Anderson-Rubin Wald test F statistic	7.35***	3.70**	3.70**	2.93**	2.93**
Stock-Wright LM statistic	7.11***	7.13**	7.13**	8.65**	8.65**

Data: Urban Household Survey (1998–2009), China General Administration of Customs (1997–2009), China Statistical Yearbook (1998–2009) and Penn World Table (PWT 7.0, 1998–2009).
Note: $N = 1670$. Column (1) shows the first stage results of Column (2) in Table 4, Column (2) and (3) show the corresponding first stage results of Column (3) in Table 4, and Column (4) to (5) show the corresponding first stage results of Column (4) in Table 4. City fixed effects, year fixed effects and regional time trend are controlled in all the regressions. Models are weighted by the start-of-period city-level population. Reported standard errors are robust and are clustered by city. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4
The impacts of imported capital goods on skill premium.

Dependent Variable	(1)	(2)	(3)	(4)	(5)
Skill Premium	OLS	IV			
Imported Capital Goods Intensity	0.03**	0.21***	0.21***	0.21***	0.22***
	(0.02)	(0.07)	(0.08)	(0.08)	(0.09)
Export/GDP			−0.14		
			(0.27)		
(Non-Capital Goods Import& Export)/GDP				−0.09	−0.13
				(0.19)	(0.25)
FDI/GDP					0.98
					(1.20)
Kleibergen-Paap rk LM statistic		6.88***	6.58**	5.43*	4.95*
Cragg-Donald Wald F statistic		54.46	6.99	3.98	2.10
Kleibergen-Paap rk Wald F statistic		7.55	3.36	1.77	4.58
Anderson-Rubin Wald test F statistic		7.35***	3.70**	2.93**	2.77**
Stock-Wright LM statistic		7.11***	7.13**	8.65**	8.47**

Data: Urban Household Survey (1998–2009), China General Administration of Customs (1997–2009), China Statistical Yearbook (1998–2009) and Penn World Table (PWT 7.0, 1998–2009).
Note: N = 1670. City fixed effects, year fixed effects and regional time trend are controlled in all the regressions. Models are weighted by the start-of-period city-level population. Reported standard errors are robust and are clustered by city. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

premium. On the other hand, as shown in Verhoogen (2008); Bustos (2011*a*), foreign markets may be more sophisticated to the extent that exporters tend to hire more skilled workers, driving up the demand for skilled workers.

Controlling for the effect of exports in the skill premium regressions, we find that our result for the impact of imported capital goods does not change much. In Column (3), we augment the baseline regression by including exports as an additional regressor, and we instrument exports using an export-weighted exchange rate. The estimated effect on capital goods imports does not change much, implying the impact is not through exports. Meanwhile, there is no evidence of exports having a separate impact on the skill wage premium in China, as the coefficient of exports is not precisely estimated.

Another concern is that the exchange rate movement may also affect the imports of intermediate inputs, which also correlate with the skill wage premium. For example, if imported intermediate inputs are more sophisticated to work with, factories may need skilled workers to work with them and, therefore, imported intermediate goods may have a positive effect on the skill premium. Controlling for imports of intermediate inputs, however, encounters us with the problem of multi-collinearity. So we sum up exports and non-capital goods imports (relative to GRP) as a general control for openness and then construct an appropriate exchange rates instrument accordingly. As shown in Column (4), the result is essentially unchanged.

The capital-goods-import-weighted exchange rate may also be correlated with foreign direct investment (FDI), which may also affect the skill premium. For example, foreign multinationals may invest more in skill-intensive sectors and favor skilled workers at the same time.[15] In this example, FDI just provides us with a channel of how imported capital goods have affected the skill wage premium. Nevertheless, to test whether FDI has an additional impact on the skill wage premium, in Column (5), we further control for provincial FDI stock relative to its total value added (gross regional production, GRP).[16] Again, the impact of capital goods imports does not change much, while that of FDI is not precisely estimated.

In addition, we also conduct two other robustness checks. First, we expect capital goods imports from more advanced countries to have a larger impact on the skill premium than those from other countries because most technological changes happen in these countries (Eaton & Kortum, 2001). Table 5 confirms this prediction. We focus on capital goods imported from the seven most advanced countries, including France, Germany, Italy, Japan, Korea, the United Kingdom, and the United States. As expected, the impact of capital goods imports from these countries is substantially larger than the impact of those from an average country. More specifically, a 10 percentage point increase in the import intensity of capital goods can increase the skill premium by 3.8 percentage points (columns 1 & 2).

Second, the assumption for identification is that our instrumental variable, the capital-goods-import-weighted exchange rate, is not correlated with the Chinese labor market through other omitted variables. This assumption held for non-USD currencies (or equivalents) for the period before 2005 when RMB was pegged to the U.S. dollar. During that period, the bilateral exchange rate changes between RMB and non-USD currencies actually reflect the exchange rate changes of these countries' currencies against the US dollar, which is exogenous to the Chinese local labor market. Using the pre-2005 sample and excluding the United States as the import origins, we find the main regression results do not change qualitatively (Table 6).

5. Mechanism

In the previous section, we have shown that cities that have imported more capital goods tend to pay a higher wage premium for skilled workers. The above results rely on the variations in cities' exposures to exogenous exchange rate changes. This section will provide more direct evidence that skill and imports of capital goods are complementary.

5.1. *The wage premium of operating imported machines*

First, we employ the China Employer-Employee Survey (CEES), which interviewed workers and employers from 500 manufacturing firms in Guangdong province in 2015. The advantage of using CEES is that it records individual workers' job responsibilities within each firm, thus allowing us to estimate within-firm wage inequality by controlling for firm fixed effects. In particular, besides their education level, the CEES asked about whether a worker is operating a machine and, if he does, whether the machine is imported or domestically made. The disadvantage is that the CEES is a cross-sectional sample of firms, so the estimates may be subject to endogenous concerns. With the aforementioned factors in mind, we run the following specification:

$$ln\left(w_{jk}\right) = \beta_1 S_j + \beta_2 \sum_{g=1}^{3} M_{jg} + X_j \delta + Z_k \lambda + \varepsilon_{jk}, \tag{6}$$

where w_{jk} denotes the wage rate for worker j in firm k, and S_j is an indicator which equals 1 if the worker has a college degree or above and 0 otherwise. $\sum_{g=1}^{3} M_{jg}$ contains a set of indicators: M_{j1} indicates whether the worker is an operator of imported machinery, M_{j2} indicates whether the worker is an operator of domestic machinery, and M_{j3} indicates whether the worker uses a computer at work. X_j contains a set of individual characteristics such as gender, occupation, working experience, and its squared term. Z_k controls for firm ownership (state, collective or private). In the most rigorous regression, we also include firm fixed effects to control for any firm-level factors that may affect workers' wages. All regressions are weighted by the inverse of the sampling probability.[17]

Table 7 presents the results. We first test in Column (1) workers' college premium after controlling for workers' characteristics, including gender, work experience (and its squared term). The result shows that college workers earn 29 percentage points more than workers without college degrees. Column (2) considers machine operators. It shows that operating a domestic machine does not raise the pay; however, operating an imported machine does. Furthermore, if a worker uses a computer at work, she will also be paid better. The college premium is now down to 25 percentage points, implying that part (about 14%) of the college premium comes from the fact that more educated workers tend to operate imported machines or use computers. Column (3) further controls workers' occupations. College premium drops by another 4 percentage points. Not surprisingly, managers, technicians, and salespersons earn more relative to production workers (the benchmark group), though the estimate of the salesperson premium is not statistically significant. Column (4) controls for firm ownership. The results remain similar to those in Column (3). Finally, in Column (5), we use firm fixed effects to

[15] The offshoring model by Feenstra & Hanson (1996, 1997, 1999), for example, shows that firms in developed countries tend to offshore their less skill-intensive production or activities to developing countries. Those activities, however, are more skill-intensive than the local activities or tasks. Thus offshoring leads to higher skill premium in both home and host countries.

[16] Unfortunately, due to data limitations, we do not have access to FDI data at the city level. We also do not have data at the province-country level to construct corresponding instruments.

[17] The sampling probability is calculated as the share of workers being surveyed relative to the total number of workers in the same occupation within the same firm.

Table 5
The impacts of capital goods imported from seven developed countries on skill premium.

	(1)	(2)	(3)	(4)	(5)
	Second Stage		First Stage		
Dependent Variable	Skill Premium		Imported Capital Goods Intensity	Imported Capital Goods Intensity	(Non-Capital Goods Import & Export)/GDP
Imported Capital Goods Intensity	0.38***	0.38***			
	(0.14)	(0.15)			
(Non-Capital Goods Import & Export)/GDP		−0.16			
		(0.22)			
Ln(Exchange Rate)$_{Kstock}$			1.00***	1.02***	0.34
			(0.38)	(0.37)	(0.25)
Ln(Exchange Rate)$_{Export}$				−0.11	−0.68**
				(0.19)	(0.28)
Ln(Exchange Rate)$_{Non\text{-}Kimport}$				−0.01	0.01
				(0.05)	(0.05)
Kleibergen-Paap rk LM statistic	6.40**	4.74*			
Cragg-Donald Wald F statistic	46.70	3.56			
Kleibergen-Paap rk Wald F statistic	6.78	1.53			
Anderson-Rubin Wald test F statistic	7.35***	2.93**			
Stock-Wright LM statistic	7.11***	8.65**			

Data: Urban Household Survey (1998–2009), China General Administration of Customs (1997–2009), China Statistical Yearbook (1998–2009), and Penn World Table (PWT 7.0, 1998–2009).
Note: N = 1670. Imported capital goods intensity is the ratio of the accumulated capital goods imported from seven developed countries (France, Germany, Italy, Japan, Korea, the United Kingdom, and the United States) to capital stock. Column (3) is the corresponding first stage results of Column (1), and Column (4) and (5) is the corresponding first stage results of Column (2). City fixed effects, year fixed effects and regional time trend are controlled in all the regressions. Models are weighted by the start-of-period city-level population. Reported standard errors are robust and are clustered by city. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6
The impacts of capital goods imported on skill premium: excluding the U.S.

	(1)	(2)	(3)	(4)	(5)
Delete imports from the United States, 2000–2004	Second Stage		First Stage		
	Skill Premium		Imported Capital Goods Intensity	Imported Capital Goods Intensity	(Non-Capital Goods Import & Export)/GDP
Imported Capital Goods Intensity	0.25*	0.69			
	(0.15)	(0.51)			
(Non-Capital Goods Import & Export)/GDP		−2.35			
		(2.41)			
Ln(Exchange Rate)$_{Kstock}$			1.82***	1.91***	0.39***
			(0.53)	(0.53)	(0.15)
Ln(Exchange Rate)$_{Export}$				−0.73**	−0.18**
				(0.30)	(0.07)
Ln(Exchange Rate)$_{Non\text{-}Kimport}$				0.04	−0.03
				(0.08)	(0.02)
Kleibergen-Paap rk LM statistic	6.97***	3.07			
Cragg-Donald Wald F statistic	30.10	0.66			
Kleibergen-Paap rk Wald F statistic	6.99	1.17			
Anderson-Rubin Wald test F statistic	2.48	2.39*			
Stock-Wright LM statistic	2.78*	6.98*			

Data: Urban Household Survey (1998–2009), China General Administration of Customs (1997–2009), China Statistical Yearbook (1998–2009), and Penn World Table (PWT 7.0, 1998–2009).
Note: $N = 661$. City fixed effects, year fixed effects and regional time trend are controlled in all the regressions. Models are weighted by the start-of-period city-level population. Reported standard errors are robust and are clustered by city. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

account for all unobserved firm-level characteristics. The college premium is about 20 percentage points. Operators of imported machines earn 7.5 percentage points more while operating a domestic machine or using a computer does not raise wages significantly. Thus, in all specifications, we find that operators of imported machines have higher wages within firms, echoing the work of Koren & Csillag (2019), who find that Hungarian workers who operate imported machines earn more than other workers.

We can also use the CEES data to examine the differences in employment structure between firms that import machines and those

Table 7
Foreign machines and wage premium of machine operator, CEES.

Ln(monthly wage)	(1)	(2)	(3)	(4)	(5)
College	0.29***	0.25***	0.21***	0.21***	0.20***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
Operator of imported machine		0.07**	0.06*	0.06**	0.08**
		(0.04)	(0.03)	(0.03)	(0.03)
Operator of machine		−0.02	−0.00	0.01	0.03
		(0.03)	(0.03)	(0.03)	(0.02)
Use PC at work		0.10***	0.07**	0.06**	0.013
		(0.03)	(0.03)	(0.03)	(0.03)
Manager			0.09***	0.09***	0.130**
			(0.03)	(0.02)	(0.03)
Technician			0.13***	0.13***	0.13***
			(0.04)	(0.04)	(0.04)
Salesman			0.06	0.06	0.11
			(0.07)	(0.07)	(0.07)
Firm Characteristics	N	N	N	Y	Y
Firm FE	N	N	N	N	Y
Observations	3959	3959	3959	3959	3959
R-squared	0.218	0.236	0.248	0.259	0.506

Data: China Employer-Employee Survey (CEES), 2014.
Note: All the regressions control for individual characteristics including gender, working experience and working experience square. The above regressions are weighted OLS, where weight for each interviewee is the firm's total number of employee who have the same occupation as the interviewee divided by the firm's total number of surveyed employee who are in the same occupation. Reported standard errors are robust and are clustered by firm. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

that do not. Table 8 shows that firms that import more machines tend to employ a higher proportion of workers who have college degrees and a smaller proportion of workers with junior high school education or less (Column 1–3). Meanwhile, they also tend to hire more technicians and fewer salesperson (Column 4–8).

5.2. Imported capital goods and firm performance

Will firms that import capital equipment perform better? To answer this question, we merge a national representative firm survey, the Annual Survey of Industrial Firms (ASIF), with the Chinese Customs' record of firm imports. Compared with the CEES dataset, the merged sample of the ASIP data and the Customs' data enables us to examine the between-firm differences. We first use the firm census data in year 2004. It provides information on firms' employment structure (i.e., the number of workers with different education levels)

Table 8
Foreign machines and employment structure, CEES.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Employment Share by Education			Employment Share by Occupation				
Dependent Variable	Junior High School or Below	Senior High School	College or Above	Manager	Technician	Salesman	Production worker	Other stuff
Imported Machine per Worker	−0.06*	0.02	0.03*	0.01	0.02**	−0.02**	−0.02	0.00
	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Machine per Worker	−0.03	0.03	0.01	0.02***	0.00	−0.00	−0.00	−0.01
	(0.03)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Exporter Dummy	0.04	−0.03	−0.01	−0.00	−0.02**	−0.02***	0.04**	−0.00
	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Ln(Employment)	−0.01	−0.01	0.02***	−0.02***	0.00*	0.00	0.02***	−0.00
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
K/L	−0.02***	0.01***	0.01***	−0.00***	−0.00***	−0.00	0.01***	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R2	0.02	0.02	0.05	0.24	0.03	0.03	0.05	0.00
N	551	551	551	551	551	551	551	551
Summary Statistics of dependent variables:								
P1	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.00
Median	0.52	0.30	0.10	0.06	0.05	0.02	0.70	0.13
Mean	0.51	0.33	0.16	0.07	0.07	0.04	0.66	0.15
P99	0.96	0.90	0.66	0.32	0.35	0.43	0.93	0.53

Data: China Employer-Employee Survey (CEES), 2014.
Note: Imported machine per worker and machine per worker are measured in 10,000 RMB per worker. Reported standard errors are robust and are clustered by firm. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9
Imported capital goods and firm characteristics.

	(1)	(2)	(3)	(4)
Dependent Variable	Share of Workers with College Degree	Computer per Worker	Ln (Wage)	Ln(Value-added per Worker)
Imported Capital Goods Intensity	0.15***	0.18***	0.04***	0.17***
	(0.01)	(0.01)	(0.01)	(0.01)
Export/Sales	−0.01***	0.00***	0.03***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Non-Capital Goods Import/Inputs	0.06***	0.07***	0.07***	0.19***
	(0.00)	(0.00)	(0.01)	(0.01)
Ln(Employment)	−0.01***	−0.01***	−0.15***	−0.42***
	(0.00)	(0.00)	(0.00)	(0.00)
Firm Fixed Effects	N	N	Y	Y
Year Fixed Effects	N	N	Y	Y
CIC 4-digit Industry Fixed Effects	Y	Y	N	N
City Fixed Effects	Y	Y	N	N
Observations	216,932	216,932	1,482,241	1,482,241

Data: China General Administration of Customs (2004) and Annual Survey of Industrial Production (ASIP, 2004).
Note: Skilled worker is defined as people with a college degree or above. Imported capital goods intensity is defined as the share of imported capital goods out of capital stock. Reported standard errors are robust and are clustered by firm. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

and usage of computers. Then we extend the sample to cover the period from 2000 to 2007. Table 9 presents the results using the following specification:

$$y_{ikmt} = \beta_1 K_{ikmt} + X_{ikmt}\delta + \mu_i + \gamma_m + \gamma_t + \varepsilon_{ikmt} \tag{7}$$

where y_{ikmt} includes a set of dependent variables for firm k in industry m at city i in year t, K_{ikmt} is the ratio of imported capital goods to its capital stock, X_{ikmt} is a set of firm-level controls, and μ_i and γ_m are city fixed effects and industry fixed effects, respectively. For regressions where data are available for more than one year, we also control for year fixed effects and firm fixed effects.

Column (1) of Table 9 shows that firms with more capital goods imports have a higher share of skilled workers (as measured by the share of workers with college degrees or above out of total employment). While the coefficient on imported input intensity is also positive, the effect is more pronounced for capital goods imports. Export intensity, however, has a negative association with the share of college workers, consistent with the observation that Chinese manufacturers' comparative advantage is labor-intensive.

Column (2) shows that firms that use imported capital goods importers also use more computers. More specifically, an increase of capital import intensity by 10 percentage points is associated with 1.8 percentage point increase in computer use per worker, as shown in Column (2) with data from 2004. A large body of the literature has examined how the computerization of U.S. firms reflects skill-biased technology change (Autor, Levy, & Murnane, 2003; Berman, Bound, & Griliches, 1994). The findings in Column (2) confirm the skill complementarity of capital goods imports.

In Column (3) and (4), we expand the sample to cover the period between 2000 and 2007. After controlling for firm fixed effects, we find that capital goods importers pay higher wages and have higher labor productivity. These findings are consistent with the findings by Bernard & Jensen (1997), who show that more capital-intensive plants hire a greater proportion of skilled workers and offer higher wages. In addition, both the export share of total revenue and import share of total inputs are positively associated with firm wage and labor productivity after we control for firm fixed effects. These findings are consistent with the finding of Dai, Maitra & Miaojie (2016).

In all specifications of Table 9, we control for firm size using total employment, city fixed effect, and industry fixed effects. Although we cannot rule out the possibility of endogeneity in the OLS regressions, the results indicate that imported capital goods are skill-biased and thus increase demand for skills.

6. Conclusion

Importing capital goods is an important way of technology diffusion because advanced tehcnology is embedded in capital goods. Recent technologies are usually skill-baised, so capital goods import could be an important driver of the rising demand for skills among developing countries. To test this hypothesis, we use Chinese data and provide both regional and firm-level evidence to show that importing capital goods increases the demand for skills. Specifically, a city at the 75th percentile of the distribution of capital goods imports has a skill premium 5 percentage points higher than a city at the 25th percentile. Furthermore, firm-level evidence shows that the operators of imported machines have higher wages. Firms using imported capital goods hire more skilled workers, use more computers more intensively, pay higher wages, and have higher labor productivity.

Our paper contributes to a growing body of literature that examines the impacts of globalization on wage inequality. While our focus has been on China, the existing literature suggests that capital goods imports could also be an important driver of the skill premium in other developing countries.

Appendix A. Appendix

Table A.1
China's top 5 capital goods importing countries/regions: 1997–2009.

Rank	Country/Region code	Country/ Region	Imported capital goods (billion USD)	Share as China's total imported capital goods between 1997 and 2009
1	116	Japan	542	21%
2	143	Taiwan, China	420	16%
3	133	South Korea	360	14%
4	502	United States	241	9%
5	304	Germany	199	8%

Data: China General Administration of Customs, 19c97–2009.

Table A.2
Correlation between each city's share of capital goods imports from major sourcing countries/regions.

	Japan	Korea	U.S.	Germany	U.K.	France	Taiwan
Japan	1.00						
Korea	−0.02	1.00					
U.S.	−0.21	−0.14	1.00				
Germany	−0.25	−0.14	−0.16	1.00			
U.K.	−0.08	−0.06	−0.00	−0.03	1.00		
France	−0.12	−0.06	−0.04	−0.07	−0.01	1.00	
Taiwan	−0.03	0.04	−0.16	−0.19	−0.06	−0.08	1.00

Data: China General Administration of Customs, 1997–2009.

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